Forecasting Distributions of Large Federal-lands Fires Utilizing Satellite and Gridded Weather Information

Haiganoush K. Preisler[1], Robert E. Burgan[2], Jeffery C. Eidenshink[3], Jacqueline M. Klaver [4] and Robert W. Klaver [3]

[1]USDA Forest Service, Pacific Southwest Research Station, Albany, CA

Tel. 510-559-6484; email: hpreisler@fs.fed.us

[2]USDA Forest Service, Rocky Mountain Research Station, retired.

Tel. 406-728-0172; e-mail: firefox@bresnan.net

[3]USDOI Geological Survey, Earth Resources Observation and Science Center, Sioux Falls, SD

Tel. 605-594-6028; email : eidenshink@usgs.gov

Tel. 605-594-6067; email: bklaver@usgs.gov

[4]Independent Research Scientist

Sioux Falls, SD

Tel. 605-594-6067

Abstract. This study presents a statistical model for assessing the skill of fire danger indices and forecasting the distribution of the expected numbers of large fires over a given region and for the upcoming week. The procedure permits development of maps on a daily bases that forecast, for the forthcoming week and within federal lands, percentiles of the distributions of: a) number of ignitions, b) number of fires above a given size, and c) conditional probabilities of fires greater than a specified size, given ignition. As an illustration, we used the methods to study the skill of the Fire Potential Index - an index that incorporates satellite and surface observations to map fire potential at national scale - in forecasting distributions of large fires.

Keywords: Fire Distribution; Fire Occurrence; Fire Mapping; Fire business; Fire danger; Fire probability maps; semi-parametric logistic regression; Spatial mapping; Statistical comparisons of fire danger indexes.

Introduction

In April 2002, the Bush administration responded to escalating costs associated with large fires by commissioning the Wildland Fire Leadership Council (WFLC) to implement and coordinate the National Fire Plan and the Federal Wildland Fire Management Policy. The WFLC consists of senior level federal, state, county and tribal representatives. The WFLC in turn chartered a Strategic Issues Panel on Fire Suppression Costs to examine wildland fire suppression activities. In their report (WFLC, 2004) this panel found that "fire suppression expenditures are overwhelmingly centered in larger fires. From 1980 through 2002 small fires (less than 300 acres [120ha]) managed by the Forest Service totaled 98.6% of the fires but represented only 6.2% of the total suppression expenditures. Larger fires (greater than 300 acres) represented 1.4% of the fires and a whopping 93.8% of the suppression expenditures." This argues strongly for a means to estimate the probability that a fire, once established, will become large.

Systems for evaluating the potential for wildfires have been in existence for some time. Examples include the National Fire Danger Rating System (NFDRS) for the United States (Burgan, 1988, Deeming et. al. 1977) and the Canadian Forest Fire Danger rating System (CFFDRS, Van Wagner 1987). These systems use weather station data and spatial interpolation to generate spatially explicit maps of the fire danger and fire weather variables. More recently some fire danger indices have been based on moderate-resolution remote sensing data (e.g., Relative Greenness, Burgan and Hartford 1993). Additionally, fire danger estimates are being produced at global to regional scales, from meteorological climate models (Roads et al. 1995). While these fire danger maps show the relative danger level between locations and dates, they do not provide managers with estimates of expected numbers of large fires. A large fire probability map is an estimate of the likelihood that ignitions will become large fires, given existing levels of fire danger variables. A weighted sum of the probabilities over a given region and time span can provide an estimate of expected numbers of large fires in a forthcoming day or week, as will be discussed in the following sections.

One procedure for estimating probabilities of fire occurrence, or probabilities of large fires, is the use of logistic regression techniques (Andrews and Bradshaw, 1997, Andrews et al. 2003, Brillinger et al. 2003, Preisler et al. 2004, Lozano et al 2007). A second procedure that takes into account spatial correlation is a modified partial Mantel correlation test as discussed in Graham et al. (2006). In our paper we will discuss how a spatially explicit logistic regression model is used to develop large fire probability maps using a particular fire potential index. This estimation and mapping technique, however, is not limited to any particular fire danger index. The same methods may be used with any other danger index (or a combination of indices) so long as spatially explicit daily historic values of the index are available for a couple of years. Additionally, we will demonstrate how estimates of conditional large fire probabilities, together with information on frequencies of fire occurrence, is used to forecast expected number of large fires in the upcoming week, for a given region.

The fire potential index (FPI) used in this study was originally developed at the U.S. Forest Service (USFS) Intermountain Fire Sciences Laboratory and the U.S. Geological Survey Earth Resources Observation and Science Center (Burgan et al. 1998). The index has been available to fire managers through the Wildland Fire Assessment System (WFAS) website (http://www.wfas.net and http://gisdata.usgs.gov/website/IVM) for several years. It was developed to incorporate both satellite and surface observations in an index that can be used to map fire potential from national to local scales, through use of a GIS. Recent advances provide the opportunity to use gridded weather forecasts rather than surface weather observations for calculation of the FPI.

The skill of the original FPI model was assessed in 1997 for the state of California for the period 1989 through 1995. Specifically, the actual occurrence of fires was spatially compared to the FPI for the same date and geographic location. The FPI was found to have a high statistical correlation with fire occurrence (Klaver et al., 1997). FPI values compared with historical fire data from 1995 and 1996 in Southern European countries, also gave good results (Sebastian-Lopez and others, 2002). The FPI was computed from 1981 through 1993 for Kalimantan Island, Indonesia and assessed by correlating it with derived fire occurrence from the TOMS (Total Ozone Mapping Spectrometer) Aerosol Index. The FPI had good correlation with the TOMS (Sudiana et al., 2003). Recently, Schneider et al. (2007) used FPI evaluated using information from Moderate Resolution Imaging Spectrometer (MODIS) data to fit a logistic regression to MODIS active fire pixels in southern California.

In the following sections we will start by describing the procedure for calculating daily FPI values on a 1km grid. Then we present some details of the logistic regression technique. We will use the probability model to assess the skill of the FPI in predicting the frequency with which ignitions develop into large fires. Finally, we will demonstrate use of the methods by producing an example large fire probability map and one-week forecasts for expected numbers of large fire events over a region.

Methods

FPI Calculations

Fire potential index maps have been produced for the conterminous U.S., at 1-km resolution for several years (WAFS site). One kilometer is the base resolution of the vegetation condition information that is derived from satellite observation (Eidenshink, 2006). The assumptions of the FPI model are: 1) fire potential can be assessed if the proportion of live/dead vegetation is defined; satellite derived vegetation greenness data (Burgan and Hartford 1993) provides a useful parameterization of this metric, 2) good estimates can be made of how close the dead fuel moisture is to the moisture of extinction, and 3) wind should not be included because it is transitory and difficult to estimate over large geographic areas.

Inputs to the FPI map are: 1) calculated dead fuel moistures (Fosberg and Deeming 1971, Fosberg 1971, Fosberg et al. 1981), 2) a dead fuel extinction moisture map to indicate dead fuel moisture contents at which fires are no longer expected to spread, 3) a maximum live ratio map to indicate the maximum proportion of living vegetation, which is assumed to have a high moisture content, and 4) weekly Relative Greenness (RG) maps (Burgan and Hartford 1993) to adjust the maximum live ratios for current conditions. The FPI algorithm has historically included estimation of only 10-hour timelag dead fuel moisture (FPI_{10}), but used this moisture to represent both 1 and 10-hour fuels, that is, fuel particles that are less than 1 inch [2.5cm] in diameter. Questions arose concerning whether or not the FPI could be improved by including moisture contents for larger fuels as well, that is, the 100 and 1000-hour timelag fuels (FPI_{1000}). These fuel particles range in size from 1 to 8 inches [2.5 to 20.3 cm].

The general form of the FPI calculation is:

$$FPI = (1.0 - deadfrac) * dr * 100.0 \qquad [1]$$

where,

deadfrac = (calculated 10-hr dead fuel moisture)/ (moisture of extinction)

dr = the proportion of the vegetation that is dead.

In the FPI_{10} model, *deadfrac* is calculated as a function of the 10-hour timelag fuel moisture, but in the FPI_{1000} model, *deadfrac* is calculated as a function of 10, 100, and 1000-hour fuel moistures, weighted according the loading in each dead fuel size class.

For this study, daily national FPI maps were calculated for the years 2001 – 2003. Meteorological data sets for the conterminous U.S. were derived from the National Oceanic and Atmospheric Adminstration North American Mesoscale (NAM) model to calculate the dead fuel moistures. The specific process for each pixel was to obtain the static inputs for extinction moisture and maximum live ratio, and current inputs for weather and Relative Greenness, then perform the calculation outlined above. FPI values range from 0 to 100. The FPI will equal 0 when the dead fuel moisture equals the moisture of extinction or the dead ratio value is 0 (all vegetation is live and fully green). The FPI will attain a value of 100 if all the vegetation is cured and the weighted dead fuel moisture is at its minimum value of 2 percent. A sample comparison of a fire danger class map and a fire potential map is provided in figure 1. Current maps may be obtained at the WFAS site.

Fire Occurrence Data

We obtained fire occurrence data from the Desert Research Institute (DRI) coarse assessment project (Brown et al 2002). The DRI wildland fire occurrence data include all reported federal lands fires from the Forest Service, Bureau of Indian Affairs, Bureau of Land Management, Fish and Wildlife Service and National Park Service. The DRI data is flagged to indicate records with no apparent problems. The fire occurrence data used in this study was for 1985 through 2005. We used only fires larger than 1 acre, and removed records that appeared to be duplicates. In the rest of the paper an ignition will refer to any fire occurrence that was at least one acre in size when discovered, and a large fire will be defined as a fire that burned more than 100 acres (40.47ha). However, the procedures described below are not limited to any specific definition of large.

Statistical Methods

Large fire probability

The relationship between FPI values and the conditional probability that an ignition, within a given one kilometer cell, in a given day, will result in a large fire, was estimated using the following logistic regression model,

$$\pi_{ij} = \Pr[Y_{ij} = 1 \mid m_{ij} = 1, x_{ij}] = \frac{\exp(\theta_{ij})}{1+\exp(\theta_{ij})}$$
$$\text{with } \log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \theta_{ij} = A_i + \beta(x_{ij} - \bar{x}) \qquad [2]$$

where the random variable Y is a binary response variable with $Y_{ij} = 1$ if there was a large fire at location j and date i and zero otherwise; m_{ij} is the number of ignitions at ij (it is assumed that only one fire can occur in a 1km^2 in a given day); x_{ij} is the value of the FPI index at location j and day i; $\bar{x}$ is the mean FPI value over all locations and span of study. A_i and β are the slope and intercepts of the logit regression line to be estimated from the data. We estimated the spatially explicit intercepts by using a two-dimensional smoothing spline function as described in Appendix A. In equation [2] when the FPI value, x_{ij}, is equal to the mean value, $\bar{x}$, the logit line is equal to the intercept. Consequently, the intercept quantifies the historic average probability of a large fire at location j, given ignition. Using a smooth surface as an estimate of the intercepts has the effect that nearby locations will have similar probabilities; consequently the spatial correlation that is bound to exist between neighboring points is partially accounted for in the model. Neighboring points are likely to have similar topography and vegetation, among other attributes that are anticipated to cause similar fire behavior (Lozano et al., 2007). One may also use a spline function to describe the second term in equation [2] i.e., the relationship between the fire danger index and the logit regression line, to account for any possible non-linearities. Non-parametric smooth functions (Hastie et al. 2001) such as splines are one way to estimate non-linear relationships without making any a priori assumptions about the shape of the relationship. In the present study, however, the relationship between the logit line and the FPI values was not significantly different from linear.

The goodness-of-fit of the estimated probabilities was assessed by producing a reliability diagram where observed values were plotted against estimated probabilities (Wilks 1995, Hosmer and Lemeshow 1989). For this comparison we used cross-validation to fit the model. Namely, probability estimates for each of the three years (2001-2003) were obtained using data only from the other two years. Next, estimated probabilities were grouped into cells of width 0.01 and the number of large fires as a fraction of the number of ignitions was evaluated for each group, to produce the reliability diagram.

Once the slope and intercepts in equation [2] are estimated, maps of conditional large fire probabilities may be produced for a given date by evaluating the probabilities in equation [2] on a 4587 by 2889 grid over the continental US using the FPI values for that date.

Predicting expected number of large fires

Conditional large fire probabilities assume that an ignition has occurred, consequently they are useful for decisions such as ceasing prescribed burn activity, implementing specific public use restrictions or making decisions on the number of fire personnel and equipment needed at a given location. In the absence of ignitions, dry fire danger conditions will not result in a fire. A product that may be of use to managers, and that can be evaluated from the large fire probabilities, is the forecasted number of large fires in a given region of interest (e.g., fire planning units, or a Geographic Area Coordination Center (GACC) region – see http://gacc.nifc.gov for a map of GACC regions). Expected number of large fires depends not only on the conditional probability of a large fire but also on the frequency of ignitions at a given location and date. For example, using 21 years of historic fire occurrence data (Figure 2) it is noted that the distribution of ignitions (fires of size > 1 acre) is not spatially uniform and the pattern differs for lighting caused fires or human (or non-lighting caused) fires. Also, frequencies of fire occurrence depend on the day of the year (Figure 3) with lighting fires being mostly in the summer months while the human caused fires do not seem to have such a large seasonal effect. These factors have to be taken into account when developing estimates of expected numbers of large fires. One possible estimate for the number of large fires is the weighted sum of the conditional large fire probabilities over a given area and time span, with weights given by the probabilities of ignition for that pixel and day. Specifically, the expected value and variance of the number of large fires in a given region, U, may be evaluated by

$$
\begin{aligned}
E(N_{kU}) &= \sum_{i=k}^{k+6} \sum_{j \in U} w_{ij} \pi_{ij} \\
\mathrm{var}(N_{kU}) &= \sum_{i=k}^{k+6} \sum_{j \in U} w_{ij} \pi_{ij} (1 - w_{ij} \pi_{ij})
\end{aligned} \qquad [3]
$$

where N_{kU} is the random number of large fires in region U for the week starting Julian day k; π_{ij} is the conditional probability of a large fire given ignition; and w_{ij} is the probability of ignition for day i and region U.

We obtained estimates of the ignition probabilities, w, by fitting a logistic regression model to the 21 years of fire occurrence data inside federal lands. A separate logistic model was developed for lightning caused fires and human caused fires and the estimate of the ignition probability was set to the sum of the probabilities from the two causes. The explanatory variables we used for the logistic regressions were location and day of the year. The specific regression used was

$$w_{ij} = \Pr[m_{ij} = 1] = \frac{\exp(c + a_j + \mathbf{b}_U \mathbf{X}_i)}{1 + \exp(c + a_j + \mathbf{b}_U \mathbf{X}_i)} \qquad [4]$$

where m_{ij} is the binary variable set to one if there is a fire (of size > 1 acre) on day i and location j and zero otherwise. Only a sample of the location/days with no observed fires was used because of the large area (all federal lands) in our study. The constant $c = \log(1/\gamma)$ in equation [4] was included in the model to adjust for the sampling proportion, γ, of non-fire locations-days (Maddaala 1992, Brillinger et al. 2003, Preisler et al. 2004); $\mathbf{X}_i$ is a non-parametric transformation of the explanatory variable day-in-year (see Appendix A). We used a transformation of the day-in-year to account for the seasonality in fire occurrence data. A different day-in-year effect was estimated for each region U. Finally, a_j is the intercept for location j estimated using a smooth surface as described above.

Given a seven-day forecast of FPI values, the conditional probability of a large fire, π, for the following seven days may be estimated by evaluating the probabilities at the forecasted FPI values. For this study we did not have forecasted FPI values, consequently we used the observed FPI values for day k as the value for all days in the forthcoming week starting on day k. In an operational setting, forecasted values will be available.

Another statistic that may be of interest to managers is the probability of at least one major fire (e.g. a fire that burns more than 5000 acres) in region U in the upcoming week. The formula for evaluating this statistic is

$$\text{Pr[at least one fire} > 5000 \text{ acres]} = 1 - \text{Pr[no fires} > 5000 \text{ acres]} = 1 - \prod_{i=k}^{k+6} \prod_{j \in U} (1 - w_{ij}\pi_{ij}) \quad [5]$$

where w_{ij} is the probability of ignition for day i location j and π_{ij} is the conditional probability of a major fire given by equation [2] with slope and intercept evaluated for the new response variable. Namely, the new response variable is set to one if the fire is greater than 5000 acres and zero otherwise.

Results and discussion

We used two versions of the FPI (FPI_{10} and FPI_{1000}) as the index for evaluating the conditional probability of a large fire. The two versions of the FPI were similar except in forested areas containing significant loads of larger dead fuels (100 and 1000-hour time-lag fuels) (Figure 4). Although FPI_{1000} values for Western forests (fuel models G and H, Deeming et al. 1977) were lower than the rest of the fuel models, the two FPI models had similar skills in predicting conditional large fire probabilities. The skill of an index was demonstrated by the significance and magnitude of the estimated slope of the logistic regression in equation [2]. An index is assumed to have no skill if the estimated slope is not significantly different from zero or, the estimate is significant but its effect on the probabilities is negligible. For the two indices tested here, both had significant slopes, however, the slope for FPI_{10} $(\hat{\beta} = 0.011 \pm 0.0012)$ was marginally larger than that for FPI_{1000} $(\hat{\beta} = 0.008 \pm 0.0008)$. For this reason, and the fact that FPI_{1000} is more difficult to evaluate, we chose to use FPI_{10} as the index for evaluating the probability maps. The slope in the present logistic regression (equation [2]) may also be used to calculate the increase in the odds of a large fire as the FPI value increases. For example, according to our results, the odds of an ignition becoming a large fire (> 100 acres) is between 1.5 and 2.0 times larger when FPI =80 compared to the odds when FPI=30. For the entire range of FPI values (0-100) there appears to be a three-fold increase in the odds of a large fire (95% CI is 2.3-3.8).

The logistic regression model appears to be a reasonable approximation for the distribution of large fire occurrences (given ignition). This is seen in the plot of observed and predicted values when cross-validation was used over the three years in our study (Figure 5).

As an example of the output of our procedures we produced four maps for August 4, 2005 (Figure 6). The maps were for (1) Estimated conditional probability (percent) of a large fire given ignition, (2) approximate 95% upper bound for forecasted number of ignitions (per 10^5) for the forthcoming week inside federal lands, (3) approximate 95% upper bound for forecasted number of large fires (per million) for the forthcoming week inside federal lands and, (4) forecasted probability (per million) of at least one major fire (a fire greater than 5000 acres) for the forthcoming week inside federal lands. A comparison between the map of the conditional probabilities for this day and the corresponding map of FPI values (Figure 1) demonstrates the need for the probability maps. While the FPI value may be similar in two regions (e.g. southern Arizona and Wyoming) the probabilities are not necessarily the same. For the example noted, the conditional probabilities in Wyoming range between 16-30% while those in southern Arizona are between 11-15% even though the FPI values in both places are around 61-70. This is because historically an ignition appears to be more likely to become a large fire in Wyoming than in southern Arizona under the same FPI values. This may be due to differences in topography, vegetation, and suppression difficulties, among other reasons that are not reflected in the FPI map, but are included in the probability model by the spatially explicit intercept of the logistic regression line. Also noted are the relatively high estimated conditional probabilities for Nevada as compared to those in Arizona. For the 21 years under study there were 1512 observed ignitions during July in Nevada federal lands with 467 (31%) of them becoming a large fire. During the same period there were many more ignitions (2504) in Arizona federal lands, however a smaller percentage (12%) developed into a large fire. This phenomenon is reflected in the third and fourth maps of forecasted numbers of large fires and forecasted probabilities of at least one major fire respectively. Because of the large number of ignitions in Arizona (see also Figure 2) more large fires are forecasted there than in Nevada, in spite of the fact that the FPI values and the conditional probabilities are larger in Nevada.

As a goodness of fit test for the forecasts, we produced one week-ahead predictions for each GACC region and for five dates during the 2003 and 2005 fire seasons. A comparison of the forecasted values with the observed values was used as a check of the skill of the methods (Figure 7). The forecasts appear reasonable - the observed total numbers of large fires per GACC region were mostly within the 95% confidence bounds of the forecasts - in most cases but four. The four largest observed values are from Rocky Mountain and the Northern Rocky GACC regions. The skill of the present procedure for predicting large fires seem to be poor for the Rocky Mountain and other regions where many of the ignitions may be due to lightning. While the present model may be able to predict above normal numbers of large fires due to dry conditions (as reflected by the FPI) it will not be able to predict these events if the above average numbers of large fires is due to an unusually large number of fire starts. The fire occurrence probabilities used in the present work are the historic frequencies of fires for a given day and region, and thus, do not change from year to year (equation [3]). However, the model skill in predicting when an ignition will become a large fire was quite reasonable, as indicated by the reliability diagram in Figure 5.

The model appears to have better skill in predicting the probability of at least one major fire (> 5000 acres) per GACC for a forthcoming week. The reliability diagram (Figure 8) was produced by assigning a value of one when at least one major fire was observed in a given GACC during a forthcoming week and zero otherwise (these are the hatch marks in the figure). Next the observations were grouped into seven cells (according to the predicted values) and the observed proportion of ones in each cell was plotted against the predicted probabilities. In this sample of cases there were 18 instances where the predicted probability was between 0.3-0.5. In six out of the 18 cases (0.33) we observed at least one fire > 5000 acres. In other words, the predicted probability was close to the observed proportion of cases.

In summary, we have presented a statistical model for assessing the skill of fire danger indices and forecasting the distribution of the expected numbers of large fires over a given region and for the upcoming week. As an example we studied the skill of the Fire Potential Index. For the three years under study, the FPI appeared to have significant skill in predicting large fire occurrence. Although the maps and the goodness of fit graphs seem promising there is room for improvement. For example, at the moment we do not have any explanatory variable (fire danger index) in the model for the probability of ignition. A fire weather index, such as probability of a lighting storm, may improve the skill of the model in predicting above average levels of ignitions. At the moment the ignition probabilities are based on historic averages (albeit the estimates are spatially and seasonally explicit). Using forecasted FPI values may also improve the model output. Finally, it may be interesting to include other fire danger indices (e.g. those in the National Fire Danger Rating System) together with the fire potential index studied here, to see if any other index, or a combination of indices, could improve the skill of the model. The advantage of the probability model presented here is that it could be used with any index, or a combination of indices and the skill of the final model may be tested immediately, by comparing estimated distributions of fire locations and sizes with those observed.

Acknowledgements

We would like to thank the Desert Research Institute Program for Climate, Ecosystem and Fire Applications for the historic fire occurrence and size data.

Appendix A

We used the R statistical package (Ihaka and Gentelman 1996; R Development Core Team, 2004) to estimate the coefficients in the logit regression lines given in equation [2] and equation [4]. In order to estimate the smooth two-dimensional function of the intercepts we first used a thin plate spline function that transforms the spatial data (x-coordinate, y-coordinate) for each fire to a matrix of the corresponding radial bases functions (Hastie et al. 2001). The required modules for fitting thin plate splines within R were downloaded from the web (Geophysical statistical project, 2002). Once the data are transformed using spline functions standard logistic regression routine may be used to estimate the coefficients with the bases matrices as the explanatory variables.

The coefficients in equation [2] may be estimated simultaneously. However, because we only had FPI values for three years, while data on fire occurrence and size was available for over 20 years, we chose to do the estimation in two steps. First we estimated the spatial intercepts using 21 years of fire occurrence data using a logistic regression model with spatial location as the only explanatory. Next we used the three years of data on fire occurrence and FPI to fit the model in equation [2] with the values of the intercepts, A_i, set to their estimates obtained from the first step. It is anticipated that the 21-year data set would give a better estimate of the historic probabilities than would the three years for which FPI is available.

The transformation suggested for day-in-year in equation [4] was obtained using a spline function to account for the non-linear seasonal effect in fire occurrence data. However, in this case we used a periodic spline function that produces similar estimates for days at the beginning and end of the year.

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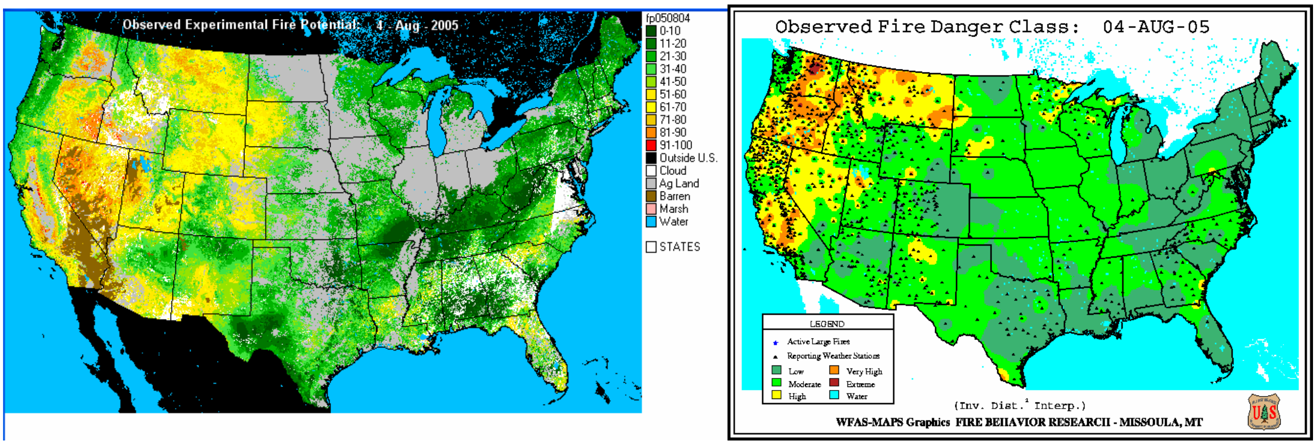

Figure 1: Observed experimental fire potential map (left panel) and the observed fire danger class map (right panel) for August 4, 2005.

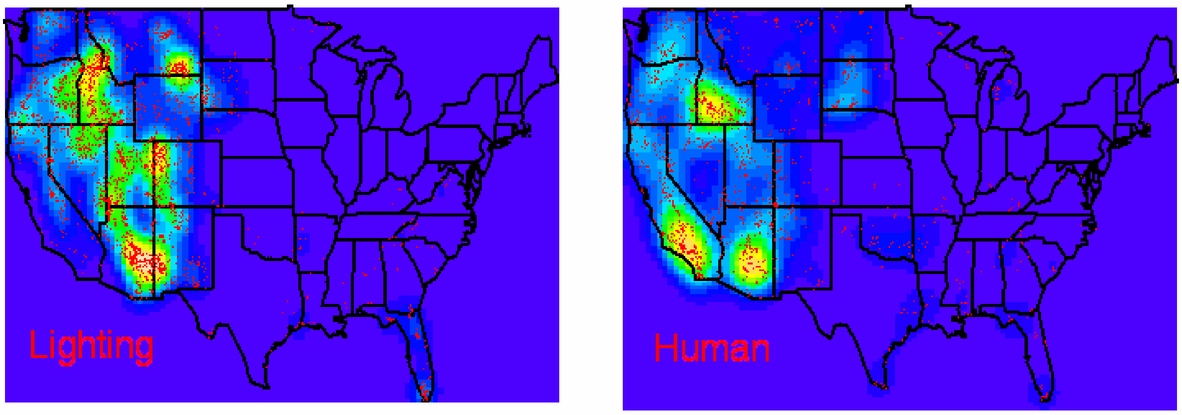

Figure 2: Locations of historic fire occurrences on federal lands. Red dots are locations of lighting and human caused fires during the month of July for the years 1985-2005. The two dimensional histogram (kernel density estimate) of the fire frequencies are displayed in the background.

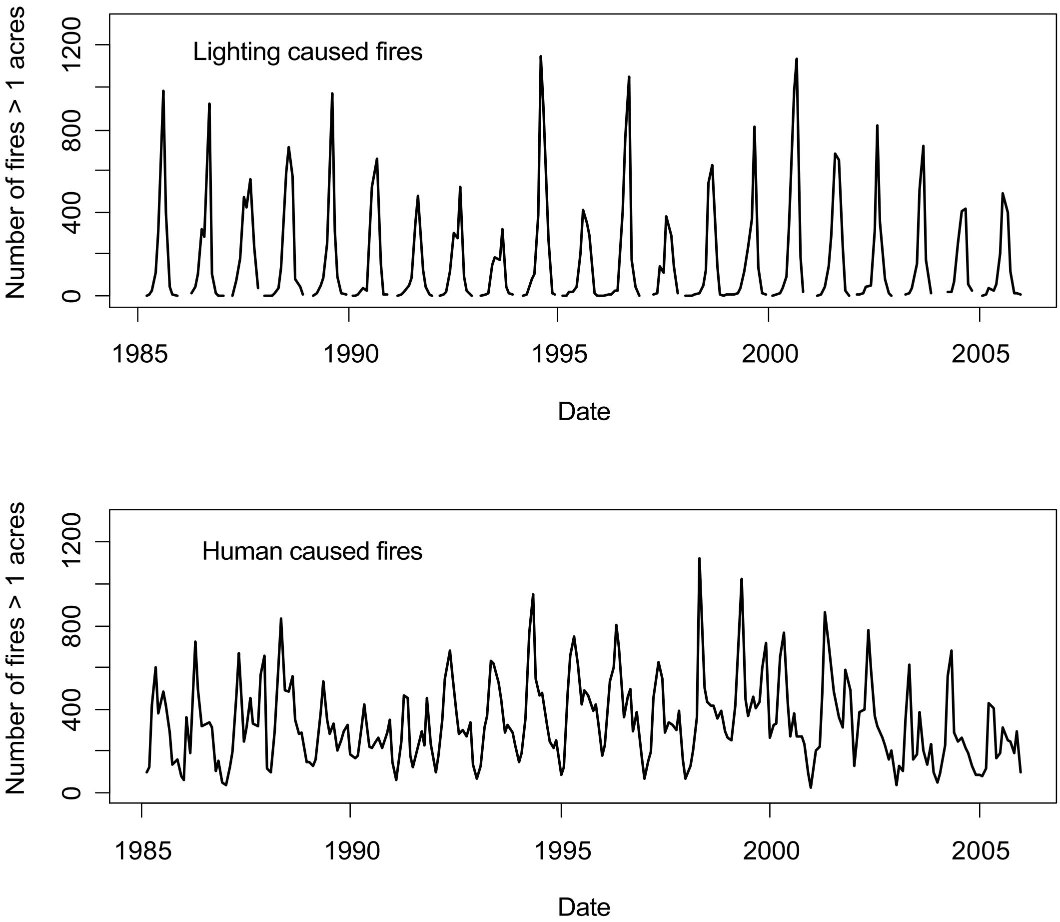

Figure 3: Observed numbers of lighting and human caused fires (size > 1 acre) per month on federal lands.

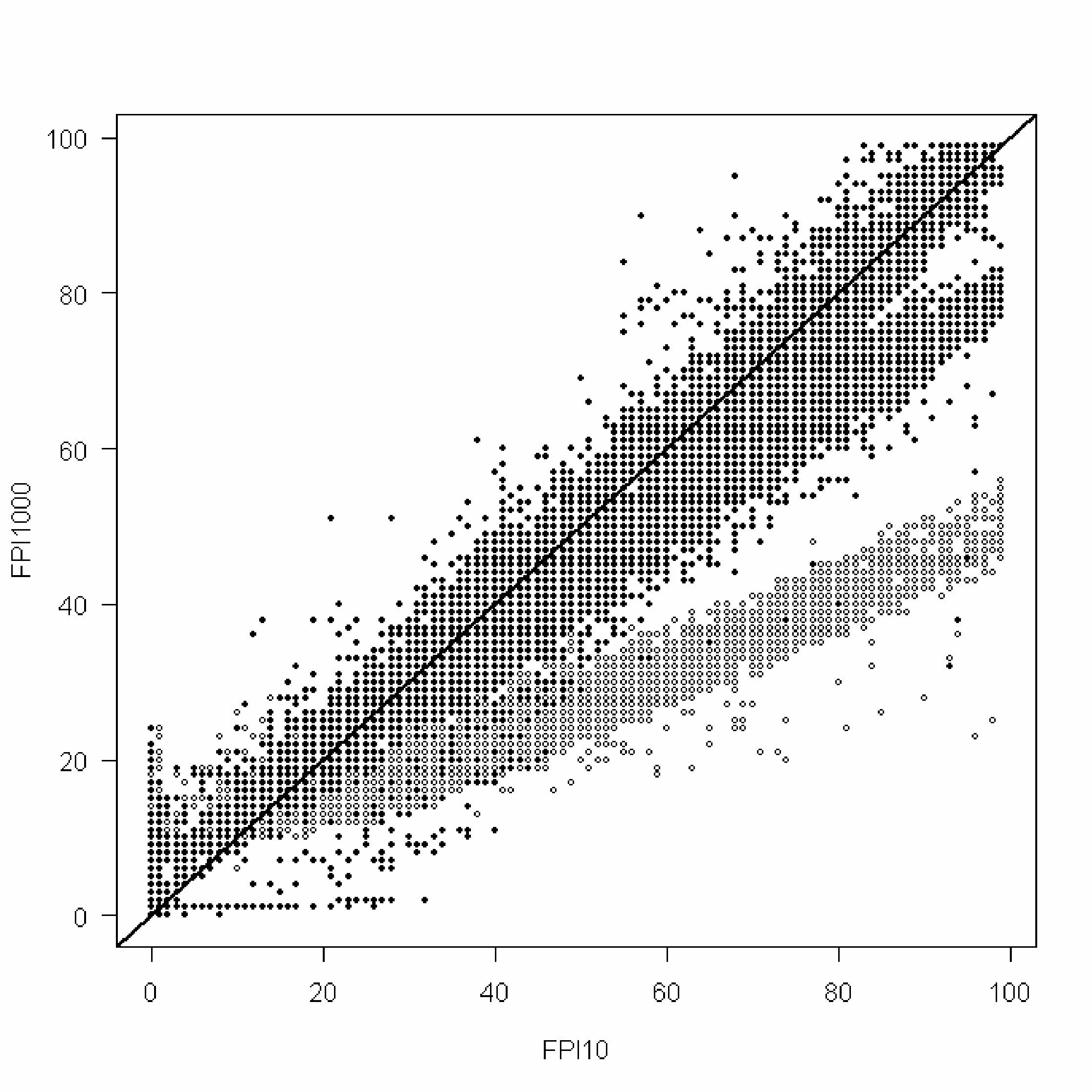

Figure 4: Ten hour (FPI_{10}) versus thousand hour (FPI_{1000}) fire potential index for fires during 2001-2003. FPI_{10} and FPI_{1000} are similar except for Western forests (fuel models G and H) where the FPI_{1000} values are smaller (open dots).

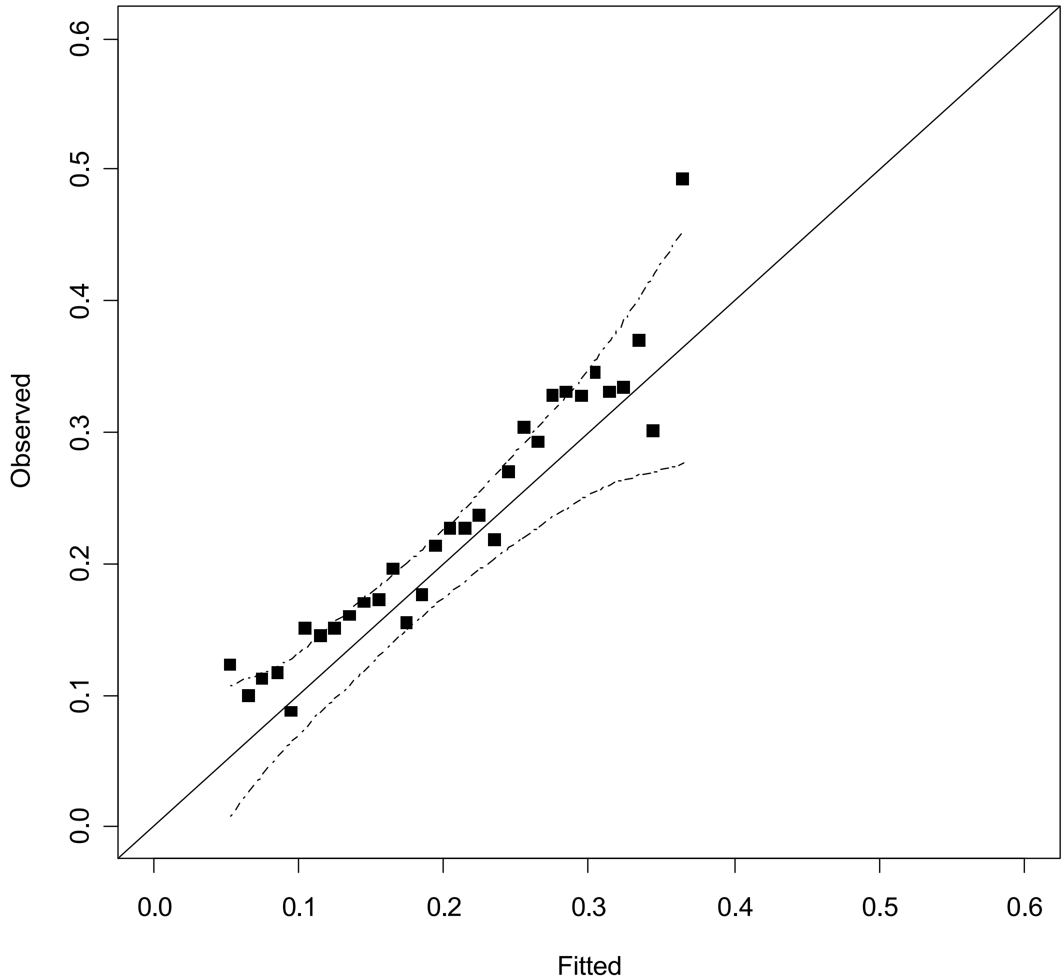

Figure 5: Observed versus fitted values of fraction of large fires as a proportion of number of ignitions. Dotted lines are the approximate point-wise 95% confidence bounds.

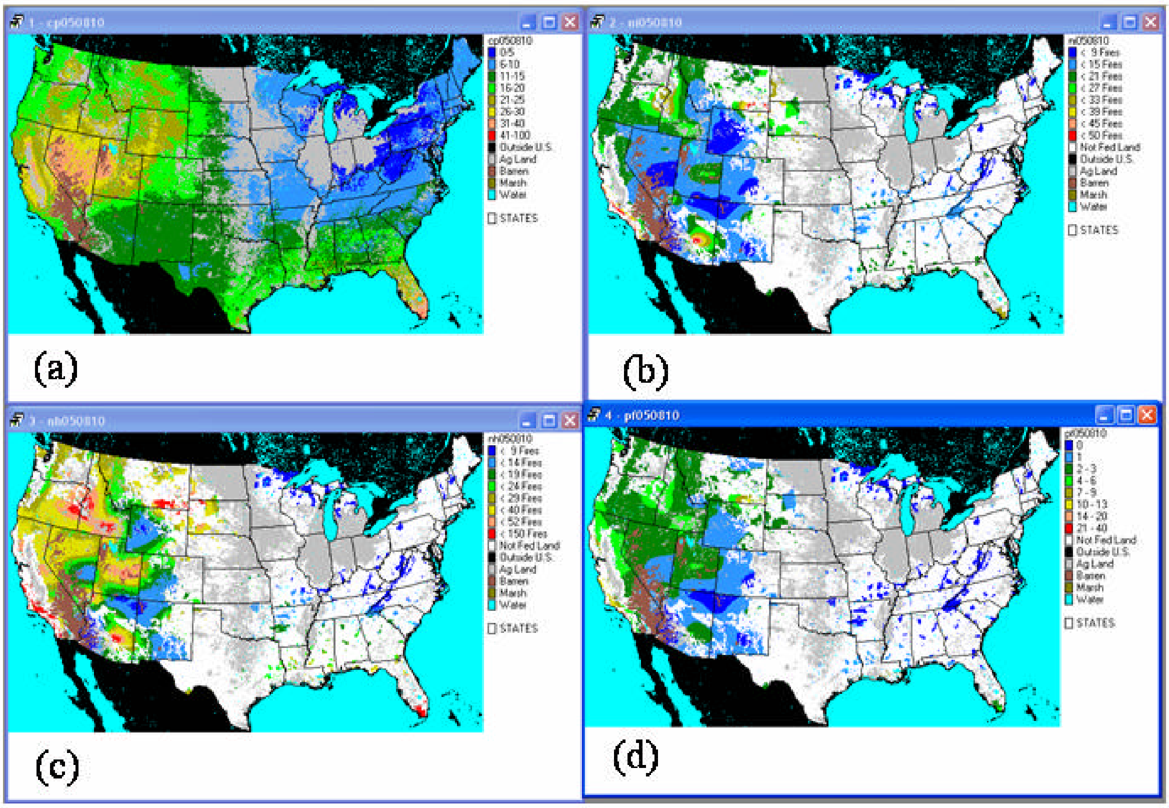

Figure 6: Four maps generated for August 4, 2005. (a) Estimated conditional probabilities (percent) of a large fire, (b) approximate 95% upper bound for forecasted number of ignitions (per 100,000) for the forthcoming week inside federal lands, (c) approximate 95% upper bound for forecasted number of large fires (per million) for the forthcoming week inside federal lands, (d) forecasted probabilities (per million) of at least one major fire (> 5000 acres) inside federal lands.

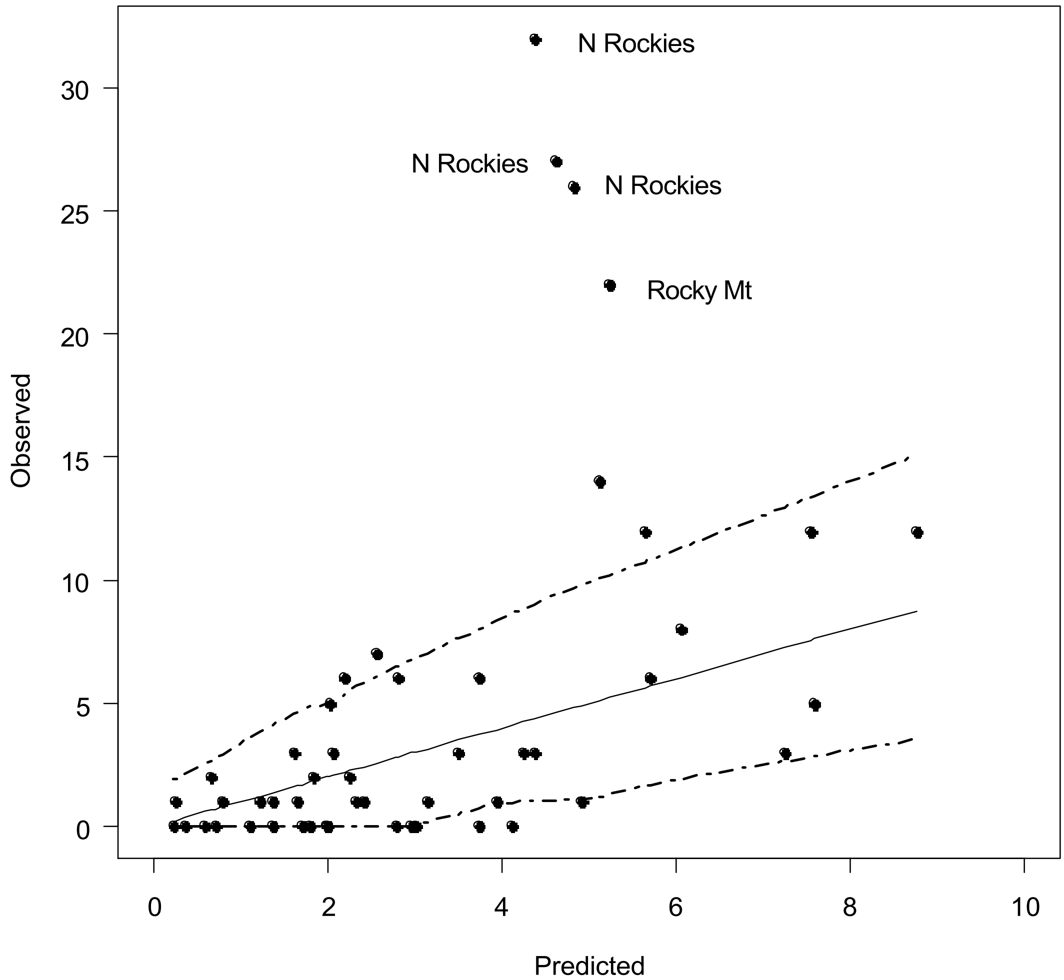

Figure 7: Observed versus forecasted total number of large fires (>100 acres) per GACC region for the forthcoming week evaluated at 5 dates during the 2003 and 2005 fire seasons. The dotted lines are the approximate 95% bounds.

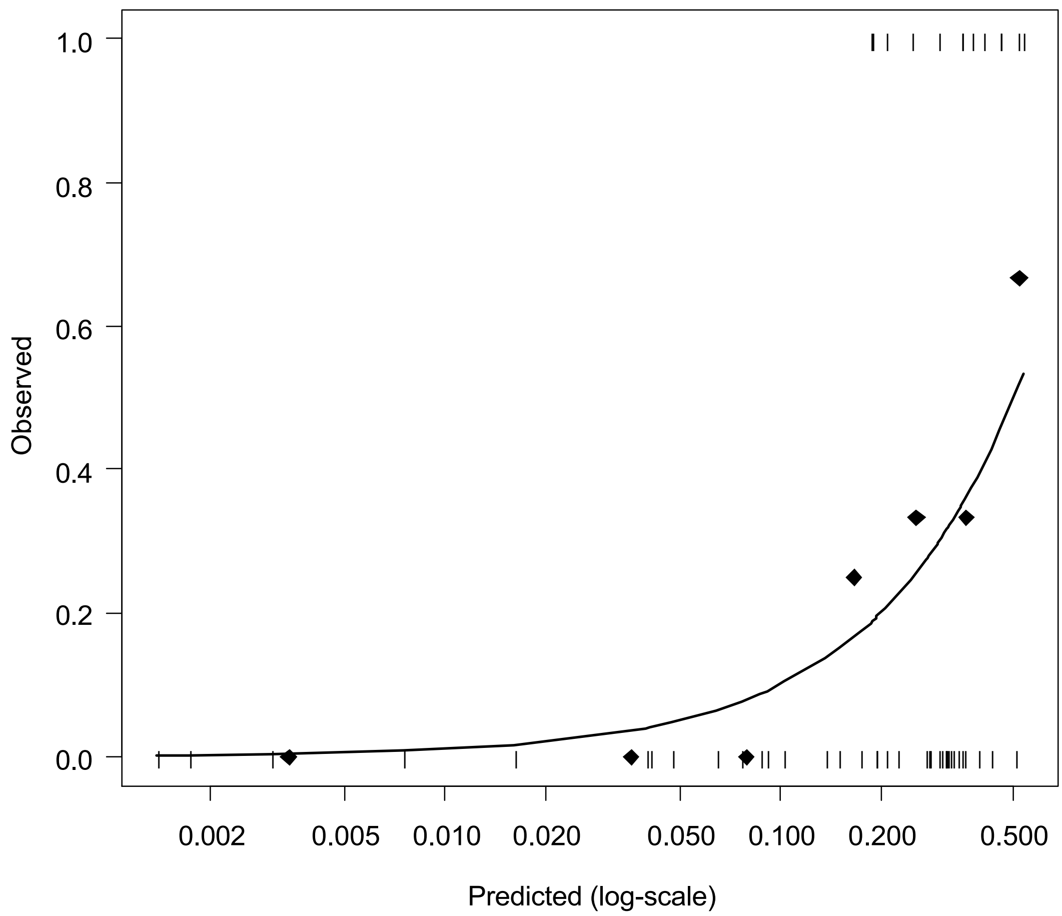

Figure 8: Observed versus predicted proportion of forecasts with at least one very large fire (>5000 acres) per GACC region in a forthcoming week. The hatch marks are the observations (0 if no fire of size > 5000 acres and 1 otherwise). Dots are the proportion of the observations when grouped into seven cells.